Resources Policy 46 (2015) 281–287

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Do commodity investors herd? Evidence from a time-varying stochastic volatility model[☆]

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ARTICLE INFO

Article history:
Received 25 July 2015
Received in revised form
22 October 2015
Accepted 22 October 2015

JEL Classifications:
Q02

Keywords:
Commodities
Herding
Time varying stochastic volatility

ABSTRACT

Commodities markets due to their unique characteristics that are they exhibit negative correlation with returns of traditional asset classes and are among the few assets that offer protection from the effects of inflation have recently garnered investors' attention especially through the development of commodity index financial products. This financialization process that started in the early 2000s and escalated after 2004 has precipitated price comovements among various types of commodities creating a proper setting for the examination of herding behavior. Employing a comprehensive dataset of investable commodities indices we examine the existence of herding behavior via static and time varying models. Our findings reveal no evidence of herding behavior according to static model. However, when rolling window analysis is in place significant anti-herding behavior is detected. These behavioral patterns are corroborated through a time varying stochastic volatility model. Our results contain significant implications for investors, commodities producers and policy makers.

1. Introduction

Over the last decades the issue of commodities markets' integration with traditional financial markets has attracted the interest of academics and researchers. The reasons behind this so-called financialization (for a discussion of financialization see inter alia Buyuksahin et al., 2010; Silvennoinen and Thorp, 2013) of commodities markets are mainly sought on the extensive use of commodities as diversification and hedging tool by financial investors. In other words, commodities have caught the attention of numerous institutional investors as a profitable alternative asset. Another related issue that might contribute to the financialization and increased variability of commodities markets is the onset of a new type of market participant namely financial index investors. For example, food commodity prices have registered an upward trend and marked multiple large peaks since 2006, the most noteworthy in 2007–2008. Upon the entry of financial index investors in the commodities futures markets a substantial portion of researchers' attention has been directed towards trading behavior of this group of investors. It is natural to expect that a large scale buying pressure stemming from financial index traders gives rise to a number of massive bubbles in agricultural futures prices. However, this assertion lacks empirical support since relevant studies fail to establish a direct link between index trading and agricultural futures pricing (Irwin and Sanders, 2011). Commodities financialization leaves room for noise trading and momentum strategies that in turn might exaggerate price increases. In light of the above trading strategies the explosive growth of commodity prices in the period from 2005 to 2008 has been placed under scrutiny. Behavioral-based explanations are often put forward by researchers (Etienne et al., 2014) in their attempt to justify these unprecedented levels of commodities prices.

This article compliments studies on the debating issue of the formation of behavioral-based patterns in the rapidly growing market of the commodities futures. Employing an extensive and updated dataset from 2002 to the end of 2014, the time varying nature of herding and anti-herding transitions patterns are examined through static and time varying methods. Static models fail to capture the dynamic nature of such behaviors; structural break tests confirm our impression for possible shifts and non linearities in the relationship of the employed variables. Therefore, a rolling window of 400 observations is used, which is consistent with the peak to trough business cycle reference dates, December 2007–June 2009, given by the National Bureau of Economic Research (NBER) for the duration of the Global Financial Crisis.

☆ We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

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http://dx.doi.org/10.1016/j.resourpol.2015.10.011
0301-4207/

Realizing that rolling window estimations could be sensitive to window-sizes, we complement the analysis using a pure time-varying regression model with stochastic volatility. In many cases, data-generating process of economic variables seems to have drifting coefficients, as well as, shocks of stochastic volatility. If this happens to be the case, then coefficients of the time-varying model with constant volatility causes the estimated time-varying coefficients to be biased, since possible variation of the volatility in disturbances is ignored (Nakajima, 2011). To avoid this misspecification, stochastic volatility is assumed in the time varying regression model. Although stochastic volatility makes the estimation difficult because the likelihood function becomes intractable, the model can be estimated using Markov Chain Monte Carlo (MCMC) methods in the context of a Bayesian inference. Further note that, unlike the rolling window regressions, the time-varying approach ensures that the entire sample period is analyzed in a time-varying fashion, without compromising the initial window. In general, the time varying regressions corroborate the findings from the rolling regressions. Specifically, the results indicate statistically significant transitions between herding and anti-herding behavior in the commodities futures markets.

Previewing our results the estimates of the static CAPM-based herding model reveal no evidence of herding behavior a finding that paves the way towards the use of a more informative, time-varying method. Motivated by substantial evidence of multiple structural breaks in the relationship of our variables as reflected in the values of proper tests we set off to employ a rolling window analysis that yields a more reliable assessment of the evolution of herding behavior. Most interestingly, significant instances of anti-herding behavior before the global financial crisis, and the absence of a statistically significant herding behavior as the window passes through the GFC period are reported. Finally, the results of the time-varying stochastic volatility model provide further support to the rolling window analysis.

The remainder of the paper is structured as follows. Section 2 presents a brief literature review. Section 3 outlines the data and the econometric methodology while Section 4 provides the results and the relevant discussion. Finally concluding remarks are discussed in Section 5.

2. Brief literature review

Prior research on herding behavior maps its way into two different strands. On the one hand there are studies that investigate group-wide herding formally defined as synchronized actions among institutional investors or certain groups of investors, such as mutual fund managers or financial analysts (Frey et al., 2014; Jiao and Ye, 2014; Kremer and Nautz, 2013; Goodfellow et al., 2009; Clement and Tse, 2005; Gleason et al., 2003; Welch, 2000; Graham, 1999; Truema, 1994; Wermers, 1999; Lakonishok et al., 1992). Still, the majority of the relevant studies explores the formation of herding patterns by measuring the shifts of stock returns dispersion in response to market movements. The theoretical foundations of this test were put forward by Christie and Huang (1995) who claimed that herding reveals itself as a market-wide phenomenon causing a common response of asset prices irrespective of available information. A growing number of studies have employed the above measures in order to explore herding effects in the US stock market (Christie and Huang, 1995) and in an international setting as well. In particular Chiang et al. (2010), Demirer and Kutan (2006) and Tan et al. (2008), investigated the existence of herding effects in the Chinese stock markets whereas Chiang and Zheng (2010) examined a large sample of 18 markets. Recently, Balcilar et al. (2013, 2014) examined the existence of herding behavior in Gulf Arab stock markets whereas Demirer et al. (2010) investigated herding phenomena is Taiwanese stocks. In a different context Gleason et al. (2004) examined herding in the US market by employing data on nine sector S&P 500 Exchange Traded Funds (ETFs) listed on the American Stock Exchange. In the same vein Economou et al. (2011) documented herding behavior for four south European markets whereas Klein (2013) examined herding behavior in US and European markets. Zhou and Anderson (2013) and Philippas et al. (2013) examined the formation of herding behavior in the US REITs market. Recently, Mobarek et al. (2014) reported herding in the European stock indices during market crises while Galariotis et al. (2015) attempted to explain the herding behavior of US and UK leading stocks using macroeconomic variables. Yao et al. (2014) found that Chinese markets A and B exhibit different levels of herding behavior. Finally, employing an augmented version of Hwang and Salmon (2004) herding model Messis and Zapranis (2014) confirmed the existence of herding behavior in five developed stock markets. Stavroyiannis and Babalos (2015) documented significant herding behavior of major European stock market indices that was dependent not only on the selected markets, but also on the time period under consideration.

Herding in commodity markets has received less attention compared to stock markets with the relevant studies reaching contradictory results. On the one hand, according to Pindyck and Rotemberg (1990) aligned trading behavior may give rise to intense comovements among commodity prices. Wiener (2006) in his study of speculative behavior in the international oil market concluded that herding might be present among specific subgroups of investors. Along the same lines, Gilbert (2009) documented some evidence of excessive behavior in non-ferrous metals markets that is driven by speculators' actions and dissipates quickly. Demirer et al. (2015) employing data on various commodities sectors report significant evidence of herd behavior only for grains. However, evidence against herding in commodity markets was provided by Chunrong et al. (2006). Adrangi and Chatrath (2008) relying on trading data documented that investors tended to follow each other but their actions do not qualify as herding behavior. Likewise, Boyd et al. (2009) employing trading data reported that the correlated actions of hedge fund managers do not pose a menace to the crude oil market. Steen and Gjolberg (2013) report no significant evidence in favor of herding and Pierdzioch et al. (2010, 2013) reported significant evidence of forecaster anti-herding behavior in oil and metals markets. More recently, Babalos and Stavroyiannis (2015) employing a rolling window analysis documented anti-herding behavior before the global financial crisis and the absence of herding or anti-herding behavior during the crisis for a sample of metals commodities futures.

3. Data and econometric methodology

3.1. The data

The dataset under examination includes the investable sub-indices of Standard & Poor's Goldman Sachs Commodity Index (GSCI) that consist of the most liquid commodity futures on 25 different commodities sectors. In particular we employ 6 futures indices from the Energy sector (Crude Oil, Unleaded Gasoline, Heating Oil, Gas Oil, Natural Gas, and Brent Crude Oil), 8 from the Metal sector (Aluminum, Copper, Gold, Platinum, Silver, Zinc, Lead, and Nickel), and 11 from the Agricultural sector (Cocoa, Coffee, Corn, Cotton, Grain, Lean Hog, Soya Beans, Sugar, Wheat, Feeder Cattle, and Live Cattle). The dataset consists of 3256 observations from 7-January-2002, when the Feeder Cattle futures index was launched, to 31-December-2014 obtained from Bloomberg. The